moves through a link if the cost is small. It hardly moves if the cost is large. This determines priority of information and the result of filtering. The cost is calculated based on past impressions the users have. In our everyday life, we usually have a time of nonsense conversations, such as greetings. We can say that they determine the cost of links in the framework of GI.

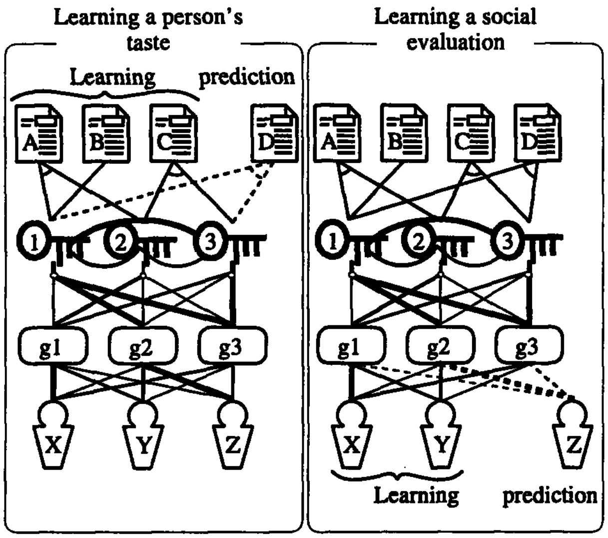

Figure 2: GIANT for News Filtering.

We describe a GIANT for news filtering as shown in Figure 2 (Yokoyama & Numao 1997), where $A - D$ are articles. $1 - 3$ are keywords or some features for content-based evaluation. $X - Z$ are readers. The nodes $g1 - g3$ represent a community or a group of subjects that evaluate articles. When it learns a person's taste, the taste is learned based on some articles. It predicts evaluation by the person of an unseen article. When it learns a social evaluation, each evaluation of articles is learned based on some subjects. It predicts evaluation by a new subject. Mixture of these two types enables more precise prediction. A community is dynamically added during the learning process, i.e., the topology of network is dynamically transformed. The network is described in predicate logical formulas to describe such transformation(Numao, Morita, & Karaki 1999). Figure 3 shows transfer rules describing the network shown in Figure 2.

If a user evaluates an article highly, the costs of links along the path are decreased. If he/she evaluates an article lowly, it is increased. This is a kind of relevance feedback. In its learning process, X first tries to train a subnetwork through a community $g1$, which represents a taste of X. When Y obtains information from $g1$, if he/she likes it, the cost of link between $g1$ and Y decreases. This means that Y participates in the community $g1$. If he/she hates it, the cost increases, and Y tries to train a subnetwork through a new community $g2$. As such, the users' evaluations cultivate some communities.

```
?- nicenews( tom ,Id).                                        Query
nicenews(Reader,Id):-
    news(Grp,Atr1,Atr2,Atr3,Atr4,Id),
    g_ap(Grp,Atr1),  g_ap(Grp,Atr2), •••,
    r_gp(Reader,Grp),
    a_ap(Atr1,Atr2),  a_ap(Atr1,Atr3),•••,
    atr(Atr1),  atr(Atr2),    •••.
g_ap( g1 ,Atr):-atr(Atr).     •••.    Evaluation in a community
r_gp( tom ,Grp):-grp(Grp).    •••.    Member of a community
a_ap( chinese ,Atr):-atr(Atr). •••.   Attribute's relation
grp(g1 ).                             Community
atr(chinese ).                        Attributes
atr(noodle ).
atr( curry ).  •••.
news(g1,chinese,noodle,shop,any,article1).                    Article
    :
```

Figure 3: Transfer Rules

Each user evaluates an article in 7 grades: 7 for the best and 1 for the worst. The system updates cost of each link c_i by c_i':

$$c_i' = c_i + (8 - E - C)c_i/C$$

where E is the evaluation by user and C is the sum of costs $\Sigma_i c_i$ along the path. This update process is based on an inference path, and related to learning based on plausible explanations (DeJong & Oblinger 1993; Widmer 1994)[2].

Kephart, Hanson and Greenwald proposed to apply *dynamic pricing by software agent* to information filtering(Kephart, Hanson, & Greenwald 2000). It can be interesting to analyze the above mechanism of information filtering from the view point of the global economy.

WWW Search Engines

The filtering method is easily applied to a WWW search engine, although information is not filtered out but retrieved. Figure 4 describes search based on a hierarchical directory(Numao & Yokoyama 1999). The interface

though it is formally inaccurate to represent an infon. Some notations for formal analysis appear in (Barwise & Etchemendy 1990). As an infon-based programming language, Prosit(Nakashima, Peters, & Schütze 1991) is constructed on Prolog.

[2]It might be analyzed based on reinforcement learning, since the process is distributed over some agents, although the authors have not tried the analysis.

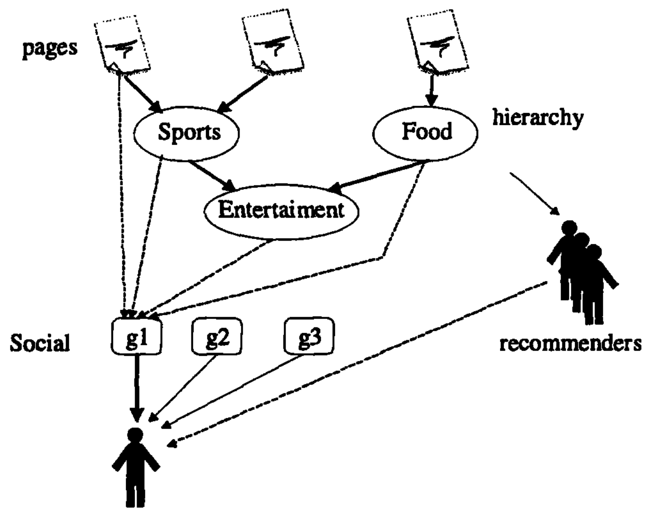

Figure 4: Searching a WWW page.

is almost the same as one of Yahoo except that it has a *recommendation button*, by which the user requests a page recommendation in the current category.

The search is based on contents, community and recommendation from another user. This method is implemented as a system called FRUIT. The authors employed the hierarchy used in Yahoo Japan[3]. This version assumes that the hierarchy represents the contents, and does not analyze texts of each page.

Each person's taste is dependent on a category of a page. For example, who have the same taste in sport may have different ones in music. The system compares evaluation in a category requested by its user.

The user's history is kept on all upper hierarchy, i.e., the reference to `/Recreation/Sports/Basketball` is recorded to the category `/Recreation`, `/Recreation/Sports` and `/Recreation/Sports/Basketball`. Therefore, the upper category keeps more reference records.

When only a few records are kept in a category, the system refers its upper category to select a good recommender. If a user wants to see pages on basketball, a recommender who has a similar taste in sports is better than one in computer.

When a user requires pages in a category, page evaluation in its lower category is used to make more precise prediction.

The system traces multiple inheritance. For example, *Johnson, Bill* appears both in `/Regional/Countries/United States/Recreation and Sports/Sports/Skiing/Johnson, Bill@` and in `/Recreation/Sports/Skiing/Skiers/Johnson, Bill`. If a user refers to *Johnson, Bill*, the system assumes that (s)he is interested in both in *Skiing* and *United States*. By this, it recommends pages in more categories.

[3]http://www.yahoo.co.jp/, which is the Japanese version of http://www.yahoo.com/.

Figure 4 shows a GIANT network representing a hierarchy. The nodes *g1*, *g2* and *g3* represent a community similar to Figure 2. Other than communities, it tries to find some recommenders who have the same taste as its user in the requested category or its upper categories.

Meta-search Engines

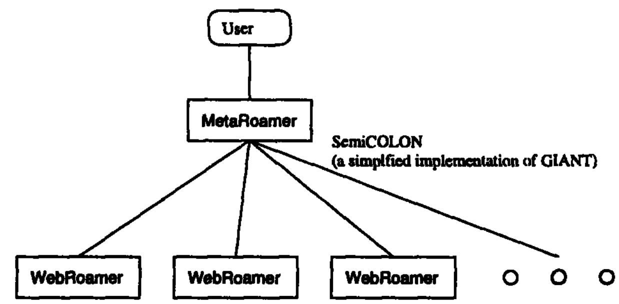

Figure 5: Meta-search engine.

A meta-search engine is a search engine for finding a good search engine(Howe & Dreilinger 1997; Selberg & Etzioni 1997; Lawrence & Giles 1998). Each search engine covers only a part of WWW pages all over the world. Meta-search integrates such expert search engines into one big search engine. The problem is how to select a search engine appropriate for user's request. Since a meta-search engine is a node in a network, it is naturally integrated into GIANT as shown in Figure 5. As such, a meta-search engine is implemented as a system called MetaRoamer(Kato & Numao 1999).

Online KARAOKE system

Online KARAOKE systems are now a popular accompaniment system to enjoy singing in Japan. It has a remote server with a huge database of MIDI files, which covers almost all popular songs. Each KARAOKE room has a terminal to download a MIDI file via a telephone line, and to sing with a microphone and speakers. The author discusses a delivering mechanism for music pieces based on preference of a user (Numao, Kobayashi, & Sakaniwa 1997). GIANT provides an intelligent network for it.

Document Reviewing

In news filtering and a search engine, information flows one way only. In email and telephone, communications are interactive. GIANT is described in a predicate logical formula, which is programmable and interactively and dynamically created as a situation changes.

Figure 6 describes a review process of funds, where agents communicate each other as error occurs in each

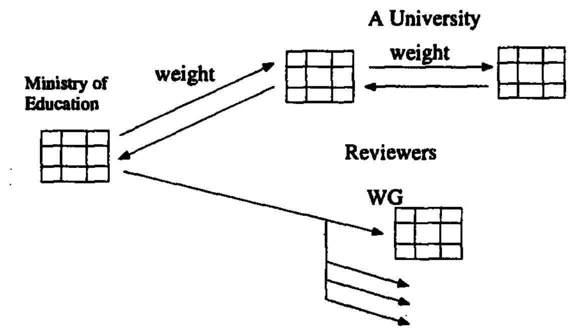

Figure 6: Global document system.

step, where some messages are neglected based on priorities.

Software Development

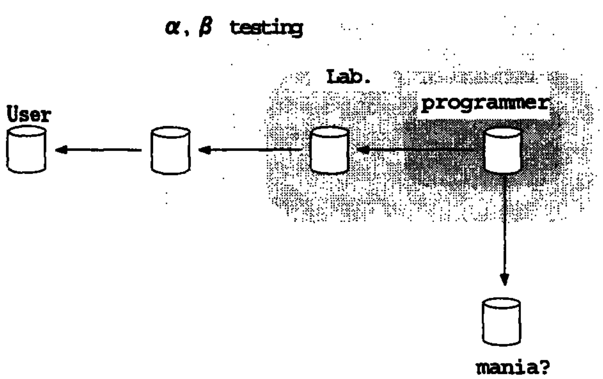

Figure 7: Software.

A bug in software is usually recognized as a difference between its specification and its coding. This view complicates a process of debugging. In reality, a bug is caused by a different view of software between its programmer and a user. GIANT offers a circulating environment of software as shown in Figure 7.

Experiments

Up to now, we have conducted experiments in news filtering, WWW search engine and meta-search engine. Here we show some results on news filtering in Figure 2. The authors selected 150 articles in Japanese from fj.food news group. They are evaluated in 7 grades by 12 subjects. A Japanese processing procedure(Mohri & Tanaka 1996) is employed to select some frequent and important keywords to be used as an attribute. Features for other attributes are length, question/answer, whether FYI(for your information) or not, etc.

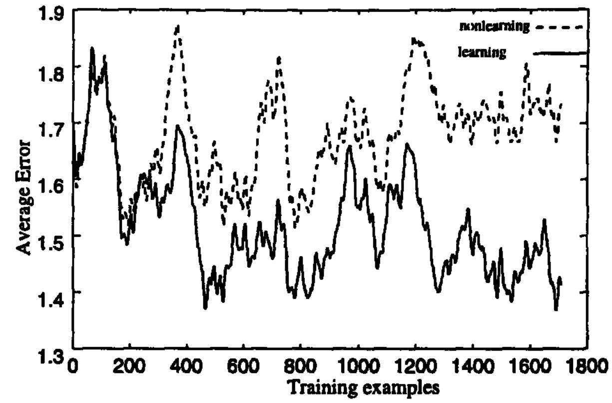

Figure 8: The Result of Learning a Person's Taste.

Figure 8 shows a learning process of a person's taste. The subjects evaluate an article in 7 grades. The system learns evaluation of 1800 articles by 12 subjects. We plot the difference between predicted evaluation of 10 unread articles and their evaluation by the subject every time the system learns an article.

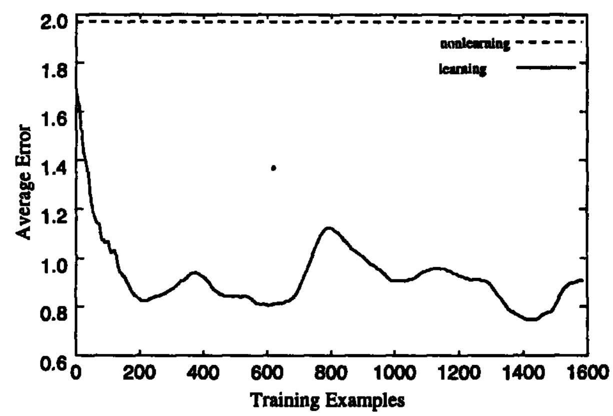

Figure 9: The Result of Learning a Social Evaluation.

Figure 9 shows a learning process of a social evaluation. The system determined a community in which a user should participate based on evaluation of 30 articles. Then, the user trained the community based on the rest articles. The result shows that the learning process converges faster than that of the personal filtering.

Organization of subjects appears as weights of links between subjects X, Y, Z and communities g1, g2, g3. The authors examine the weights and observe that GIANT organized the 12 subjects into the following 5 communities:

- Excluding subject 6. Its members like Asia, questioning and short articles, but hate answering.

- Including 3, 5, 10, and excluding 2, 9, 12. Its members like drinking, fruit, providing FYI and answering, but hate fish.
- Including 4, 11, and excluding 6, 9, 12. Its members like fish, noodle and Japan, but hate drinking.
- Including 1, 2, 11, and excluding 6. Its members like meat, discussion of ingredients and Japan, but hate restaurants.
- Including 5, 7, 8. Its members like fish, restaurant, Asia and a near location, but hate long articles.

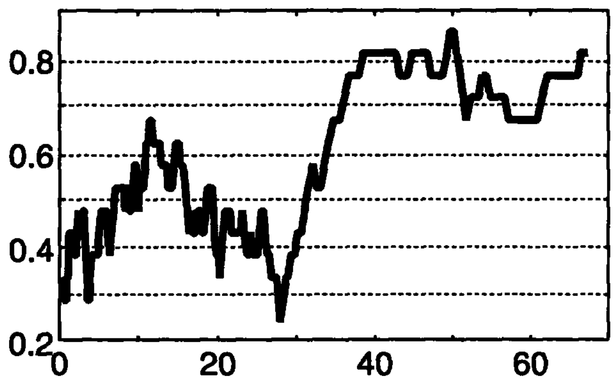

Figure 10: The click rate for WWW search results.

In the case of WWW pages, we need a search engine instead of an article filtering system. We apply the same mechanism as the above to search pages. A WWW search engine creates and shows some link pages to its user, who clicks only some of the links. Since it is hard to obtain evaluation of each link from a user, the authors collect its click rate. In the experiment, 65 users search 2400 times in one month. Figure 10 shows the click rate of 15 users who refer the engine more than 50 times. The click rate increases from 0.4 to 0.8 as the engine learns their preference.

For verification of meta-search shown in Figure 5, the authors prepare 8 search engines, which major in winter, music, games, movies, gourmets, local areas, leisure and health, respectively. Figure 11 shows percentage of collect selection in 50 test examples. The result is an average of 10-fold cross validation for 500 data. It shows that MetaRoamer selects a correct search engine in more than 50% cases.

Conclusion

We propose an idea of Global Intelligence as a hybrid system of users and a computer network GIANT, where a dynamic network described in a logical formula is a key feature. Global Intelligence makes it possible to combine several systems smoothly in a distributed manner. Table 1 shows such a combination in FRUIT.

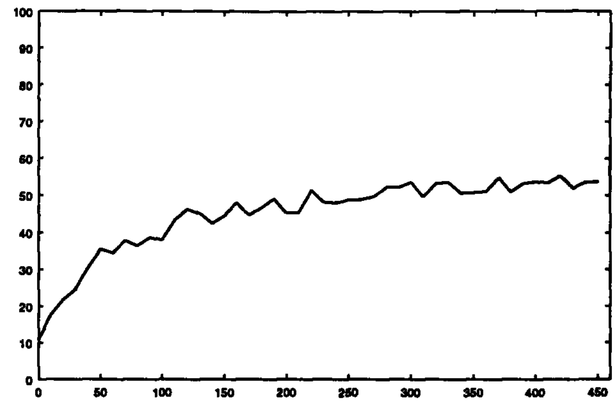

Figure 11: A result in meta-search.

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Table 1: Comparison of FRUIT with others

	Community	Recommenders	Contents	Request	
FRUIT	Yes	Yes	Yes	Yes	hierarchy
WiseWire (WiseWire)	Yes	No	Yes	Yes	commercial service
Fab (Balabanovic & Shoham 1997)	No	Yes	Yes	No	hybrid system
Phoaks (Terveen *et al.* 1997)	Yes	No	Yes	No	News&WWW
ReferralWeb (Kautz, Selman, & Shah 1997)	Yes	No	No	No	Assuming Referral Chain
Siteseer (Rucker & J.Polanco 1997)	No	Yes	No	Yes	Bookmark agent
(Mori & Yamada 1997)	No	Yes	No	Yes	Bookmark agent
GroupLens (Paul *et al.* 1994; Joseph *et al.* 1997b)	No	Yes	No	No	News
Ringo (Shardanand & Maes 1997b)	No	Yes	No	No	Recommend music
WebWatcher (Joachims, Freitag, & Mitchell 1997)	No	No	Yes	No	HTML, Reinforcement Learning
LASER (Boyan, Freitag, & Joachims 1996)	No	No	Yes	No	HTML, TFIDF
(Mizoguchi & Ohwada 1996)	No	No	Yes	No	Inductive Logic Programming
NewT (Maes 1994)	No	No	Yes	No	GA
SYSKILL&WEBERT (Billsus & Pazzani 1997)	No	No	Yes	No	Bayesian Classifier (Duda & Hart 1973)

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